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Rank-based alternatives to mean-based ensemble models of satisfaction with earnings: Comment on Putnam-Farr and Morewedge (2020)

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Abstract

How much satisfaction do we derive from a new salary or from receiving a bonus payment in an experiment? People do not judge monetary amounts in isolation but compare them to other amounts – judgments are context-sensitive. A key question is, however, *how* context affects judgment. Across eight experiments, Putnam-Farr and Morewedge (2020) show that people's self-reported satisfaction with a sum of money is predicted by the difference between that amount and the highest or lowest amount received by others. The authors find no evidence that people's judgments are sensitive to the ranked position of a monetary amount among other rewards. Putnam-Farr and Morewedge explain their results with reference to the ensemble representation literature, which shows that people can accurately estimate summary statistics, such as the maximum or mean, of stimulus distributions. In this commentary we argue that their proposed interpretation is inconsistent with extensive theoretical and empirical research showing that judgments of stimuli reflect the relative ranked position of those stimuli within a comparison context. Building on this research, we show that the experimental results reported by Putnam-Farr and Morewedge can be explained on the assumption that people use contextual information to infer a distribution of monetary amounts and judge individual amounts by their relative ranked position within that inferred distribution. This Inferred Distribution Theory (IDT) accounts for empirical results reported in the original paper while remaining consistent with the general and well-established principle of rank-based judgment.

Keywords: wage satisfaction, happiness, context effects, rank, mean, ensemble perception

Introduction

It is well established that people's judgments and decisions about economic quantities are strongly influenced by the context of available options (see Lichtenstein & Slovic, 2006, for a review). The systematicity and robustness of context effects has motivated development of many recent formal models of choice behavior. The key property of these models is that the subjective value of a given stimulus (e.g., an attribute or consumer good) is influenced by other stimuli in the choice set. Subjective values are therefore inherently context-relative (Bourgin et al., 2019; He et al., 2020).

Putnam-Farr and Morewedge (2020; henceforth PF&M) present a novel model of context-dependent judgment to explain how satisfaction with a monetary amount is influenced by the monetary amounts received by other people. We illustrate using salaries as an example. According to PF&M, people first determine whether a to-be-judged salary is above the average of all salaries in the comparison context. If the target is higher than this average, its subjective value is determined by the distances between the target and the highest (the "extreme") salary and between the target and the average salary. If, on the other hand, the target is lower than the average, the target value is compared to the lowest salary in the distribution instead of the highest. In support of their model, PF&M draw on the extensive literature on ensemble representation which shows that people are capable of accurately estimating summary statistics of many numerical and physical stimuli (e.g., Whitney & Yamanashi Lieb, 2018).

PF&M present evidence in favor of their model from a series of experiments in which participants indicated their satisfaction with monetary amounts in varying comparison contexts. Across eight experiments the authors varied the extreme and mean values of monetary outcomes obtained by others. People's judgments of an outcome were best explained by that outcome's distance from the extreme values and from the mean. Crucially for the purpose of the present commentary, the authors found no evidence that people's satisfaction judgments were affected by the relative ranked position of the target amount when this position was experimentally varied between the conditions (in PF&M's Experiment 3) and have therefore proposed a model that does not predict rank effects. Although PF&M failed to find an effect of rank in their study when mean and range (but not standard deviation or variance[1]) are controlled, many previous studies have found effects of rank and we review these in the next section. We then present a model that incorporates rank and accounts for PF&M's data.

Ensemble Representations and Ensemble Judgment

PF&M's model is based on a large body of research showing that people are very good at estimating summary statistics, especially the arithmetic mean, of a set of stimuli. For example, Ariely (2001) found that people can estimate the average size of a collection of circles despite having poor recall of individual circles. More recently, Yamanashi Lieb et al. (2020) demonstrated that people can accurately estimate the mean market price of a diverse set of consumer goods flashed on-screen for 1 second. The high accuracy of ensemble judgments has now been shown across numerous domains such as tone loudness, emotionality of faces, and orientation (Alvarez, 2011; Whitney & Yamanashi Leib, 2018). PF&M propose that ensemble representations also underpin judgments of satisfaction with monetary amounts, thus extending the approach to judgment of economic quantities[2].

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[1] As noted by an anonymous reviewer, maximum wage and wage standard deviation are not independent in PF&M's experiments. Thus standard deviation was not controlled for and, as will be discussed, the confound can lead to the results they report.

[2] Their approach should not be confused with cognitive models that have been proposed to explain how people achieve a high level of accuracy when estimating summary statistics of a stimuli set. PF&M take rapid and accurate ensemble representation as a given, and focus on a

In its adoption of a mean-based ensemble approach, PF&M's proposal highlights a contrast between the *ensemble model* of PF&M and *rank-based* models. These two classes of explanation differ fundamentally in their assumptions about what information is used when context-based judgments are made. In PF&M's ensemble model, summary mean and max/min values are used to quantify the difference between a target stimuli and extreme values, and this difference underpins valuation. Similarly, according to Helson's Adaptation Level Theory (1964), judgments of economic quantities are made with reference to one salient value which may (although need not) be the mean. In contrast to Helson and PF&M's approach, other models imply that the relative ranked position of an item in a (sample) distribution of contextual items influences judgment or valuation. Existing models that assign a major role to stimulus rank include Range Frequency Theory (RFT; Parducci, 1965) and the Decision by Sampling (DbS) model (Stewart et al. 2006)[3]. In DbS, judgments are based solely on the relative ranked position of a stimulus within a comparison set, whereas according to RFT judgments reflect a compromise between the relative ranked position of a stimulus and the position that the stimulus occupies within the range bounded by the highest and lowest contextual stimuli (see Brown & Walasek, 2022, for discussion of the relationship between DbS and RFT). Thus for present purposes the critical feature of PF&M's proposal is not that it assigns a role to the extreme values within a contextual distribution — other

model which relies on ensemble representation to arrive at some evaluative judgment (here satisfaction with monetary amounts).

[3] Some rank-based accounts that we discuss are also process models in that they explain *how* judgments are made. For example, the Decision by Sampling model specifies how the relative rank position of stimuli arises through a series of ordinal binary comparison between a target value and other items sampled form memory. Although PF&M describe a process model, the authors do not formalize it. For this reason, our primary focus is on the type of information used to account for the effects of context on judgment.

models (such as RFT, and indeed extended versions of DbS) also imply such a role. Rather, the key element is PF&M's claim that there are no effects of relative rank.

A large body of research over half a century has explored the relative importance of rank in judgment. Initial evidence in favor of relative rank effects came from studies of psychophysical judgments, in which people estimate squares to be larger and lines to be longer when such stimuli occupy a higher rank in their context (e.g., Parducci, 1965; Parducci, 1963; see Parducci, 1995, for a discussion of this earlier research). Subsequent studies have evidenced the importance of relative rank in higher-level cognitive judgments: rank-based rather than mean-based comparisons predict, for example, judgments of depression from relative rank of depressive symptoms, judgments of concern with debt from the relative rank of debt, judgments of healthiness from the relative rank of calorific content, and judgments of student performance from the relative rank of exam scores (Aldrovandi et al., 2015a; Aldrovandi et al., 2015b; Mellers & Birnbaum, 1983; Melrose et al., 2013). Research that has found rank effects does not rule out the range and mean effects predicted by PF&M's model (indeed, range and mean effects can be difficult to entirely tease apart even when varying contextual distributions). However, results demonstrating that rank can affect judgment do rule out the particular model presented by PF&M, which does not include a rank component.

PF&M test the predictions of their model for satisfaction judgments with monetary bonuses. Early work in this domain suggested that satisfaction with a wage is determined by the relation of that wage to the mean wage in a comparison set (e.g., Clark & Oswald, 1996). More recent research, however, has suggested instead that the relative ranked position of an income within a comparison set determines judgments of both wage satisfaction (Brown et al., 2008) and life satisfaction more generally (Boyce et al., 2010). The latter finding has been replicated in many countries (Macchia et al., 2020) and is consistent with effects of income inequality on income/well-being gradients (Quispe-Torreblanca et al., 2021). Similarly to PF&M, Brown et al. (2008) gave students hypothetical wages but presented them in the context of different contextual wage distributions. The students were then asked how happy they would be with their wage. Students reported that they would be happier with their hypothetical wage when the relative rank of that wage was high in the contextual distribution[4]. These results are in line with other work that shows an influence of wage rank and of payment distribution on job satisfaction and happiness (Kifle, 2014; Tripp & Brown, 2016). Such results cannot, however, be explained by the ensemble model of PF&M which predicts that subjective ratings of happiness with one's wage will not reflect changes in wage rank as long as the mean and maximum wage remained constant.

Given the importance of their theoretical interpretation and the apparent difficulty of reconciling it with conclusions from previous literature, in this reply we offer an alternative explanation of PF&M's results. We explore whether PF&M's results can be explained on the hypothesis that participants are inferring a distribution of monetary amounts and evaluating a given amount based on its position in this inferred distribution. The idea that people value an object based on its position in an inferred distribution has been successfully used to explain a broad range of empirical results in judgment and decision-making (Birnbaum, 1982; Birnbaum, 1999; Johnson & Mullally, 1969; Leong et al., 2017; Leong et al., 2019; McKenzie & Sher, 2020; Sher & Mckenzie, 2014). In a recent model of choice by Ronayne and Brown (2017), for example, it is the estimate of the rank of an attribute value in an inferred distribution, rather than its rank within the observed sample, that determines its attractiveness. We therefore hypothesize that different contexts (the mean and endpoints specifically) influence satisfaction judgments by altering the wage distribution that people infer. We explore this idea in the following section.

[4] This experiment also found effects of range.

Inferred Distribution Theory

We propose a simple alternative explanation for the results that PF&M (2020) report, which we refer to as Inferred Distribution Theory (IDT). IDT implies that participants infer a distribution of monetary amounts from a sample of monetary amounts they recall and, crucially, that they judge their satisfaction with a monetary amount based on its rank within the distribution that they have inferred. More formally, we assume that the value of any given wage, x_i, for any given participant, is computed as $u(x_i) = \int_{-\infty}^{x_i} f(x)dx$ such that the value of a wage is given by its position in the cumulative distribution function of the wages. The inferred distribution is assumed to be Gaussian: $f(x) = N(\mu,\ \sigma)$ with μ being the participant's estimate of the mean wage and $\sigma = \frac{max - min}{y}$ where max is the participant's estimate of the maximum wage, min is the participant's estimate of the minimum wage, and *y* is a free, population-level, parameter estimated using maximum likelihood estimation[5]. *r,* the response between 1 and 7, is produced by linearly transforming the wage's inferred percentile to a response: $r = 1 + u(x) * 6$. We make predictions using this simple instantiation of the IDT with the aim of presenting a comparison of these results to those

[5] The parameters γ and σ (σ represents response standard deviation, estimated to be 1.69) were estimated using maximum likelihood estimation, assuming a Gaussian distribution of response noise and assuming no difference between conditions or experiments. The likelihood was calculated using responses at the individual level after pooling participants from PF&M's Experiments 2-7.

reported by PF&M[6]. Note that although we use participant-provided endpoints estimates to estimate the standard deviation of individuals' inferred distributions, we do not suggest that people explicitly represent or use endpoint estimates when making judgments. In summary, we derive IDT predictions of happiness ratings for each person in the PF&M study based on their own personal estimates of mean wage and wage range.

Predictions from the IDT model replicate the trends we see in the original data from PF&M (2020). Figure 1 displays response predictions from IDT alongside the original data for Experiments 2 – 7. The figure shows that IDT reproduces the group differences reported by PF&M, including those in Experiment 3 where the rank of the target amount was manipulated between conditions. Crucially, all predicted happiness ratings were generated by a rank-based model of subjective judgment.

Predictions of IDT are lower than the average ratings reported by the participants in each condition, by an amount that is approximately constant across all experiments and conditions. While it would be trivial to add an intercept to the model we have described, we do not believe that such an addition would add explanatory value. A better fit to the data would also be obtained by extending IDT by assuming that people may infer more complex distributions than the simple Gaussian (e.g., lognormal or Pareto, better to reflect possible priors about wage distributions). These extensions would be reasonable in light of research showing that people can represent distributions that are skewed or multimodal (Zhu et al., 2017), and more complex distribution representations would be necessary for an extended

[6] For comparability with the work of PF&M we refer to judgments of happiness with a wage. However, the model can be applied to judgments of any monetary quantity (e.g. bonus amounts in the experiment).

version of IDT, unlike the current version, to be able to predict the common double-crossover of judgment functions seen in experiments (e.g., Birnbaum, 1974).

Overall, our results support the idea that the influence of different experimental conditions on happiness ratings are driven by the way certain conditions (higher maximum wage) shift the entire inferred wage distribution upwards, placing the to-be-judged wage at a lower percentile.

Discussion

In conceptualizing the value of a wage as its perceived position in a wage distribution, IDT reconciles disparate literatures showing a) that the rank-based coding of objects within inferred distributions reflect efficient coding of magnitudes (Bhui & Gershman, 2018; Heng et al., 2020), b) that valuation based on rank in an inferred distribution can explain a number of context effects in choice behavior (Ronayne & Brown, 2017; Sher & McKenzie, 2014), c) that the relative rank of an object becomes less influential on its valuation in more uncertain conditions when inferred distributions might be less accurate (Bhui & Gershman, 2018; Wedell & Parducci, 1988) and d) that people generally perform well when estimating ensemble information such as means and variances (Alvarez, 2011; Haberman et al., 2015; Whitney & Yamanashi Leib, 2018). The conceptualization of perceived value as rank in an inferred distribution is therefore not unique to the IDT model.

There are alternative models that would make similar predictions to IDT, but we differentiate here between IDT, RFT and the model presented by PF&M as these models make different assumptions about the relevant underlying psychological process. RFT assumes that absolute stimulus values are mapped onto two different scales which are then weighted and combined. A model that includes mean, maximum and minimum values, such as the one proposed by PF&M, demands the recall of contextual wages, the calculation of means, and then the weighting and combining of these values. The IDT model assumes a different process in which participants recall as many contextual wages as possible and then infer a distribution from these recalled contextual wages. Research into efficient coding has proposed plausible processes, such as rank-based neural coding or perceptual noise, that could result in people behaving as if they have inferred a distribution of contextual stimuli (see Bhui & Ghershman, 2018; Frydman & Jin, 2021; Heng et al., 2020).

Finally, we note that IDT can also predict range effects: The effect of changing contextual endpoints when stimulus rank is held constant can be captured by changes in the resulting inferred distribution. Previous work has similarly explained range effects as resulting from changes to inferred distributions (Brown et al., 2015a; Brown et al., 2015b).

In summary: Judgment of happiness with monetary amounts is highly context sensitive – judgements emerge from comparison with other amounts (e.g., amounts received by others). Both our rank-based IDT and the ensemble-based model put forward by PF&M imply context-sensitivity. Yet, the two accounts differ significantly with respect to what information about the comparison context underpins people's judgments. Here we have shown that a rank-based process can give a good account of judgments of satisfaction with monetary amounts. While PF&M offer evidence apparently inconsistent with pure rank sensitivity, their data do not rule out rank-based coding of information. Whereas people are able to estimate summary statistics (e.g., mean, variance), more research is required to determine under which conditions people rely on those summary statistics when making judgments about socio-economic quantities.

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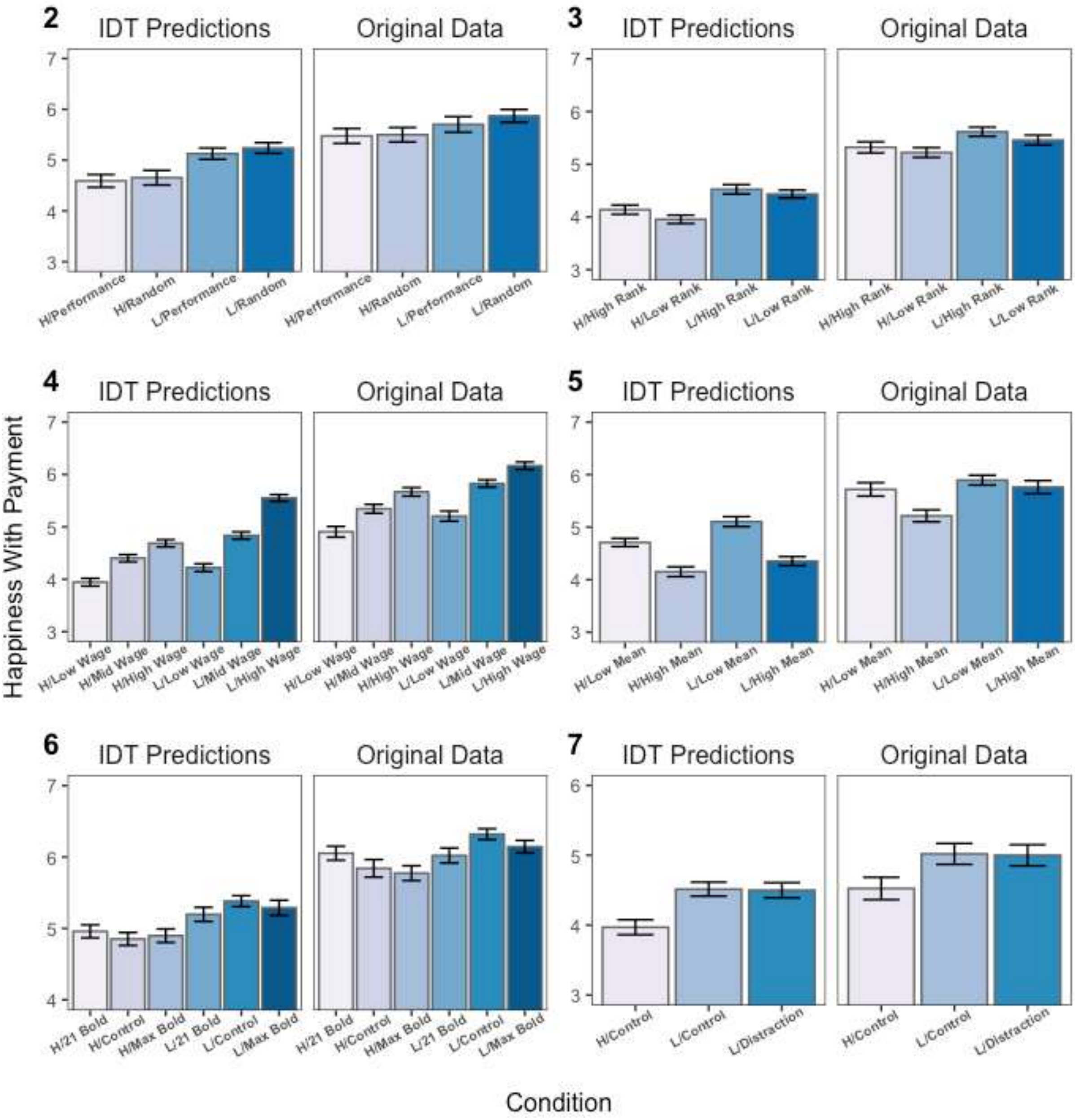
Figure 1

IDT Predictions and PF&M Data for Mean Happiness in Experiments 2 to 7 for Each of the Different Experimental Conditions



Note. L and H refer to low maximum and high maximum wage conditions, respectively. The error bars represent 1 standard error from the mean.